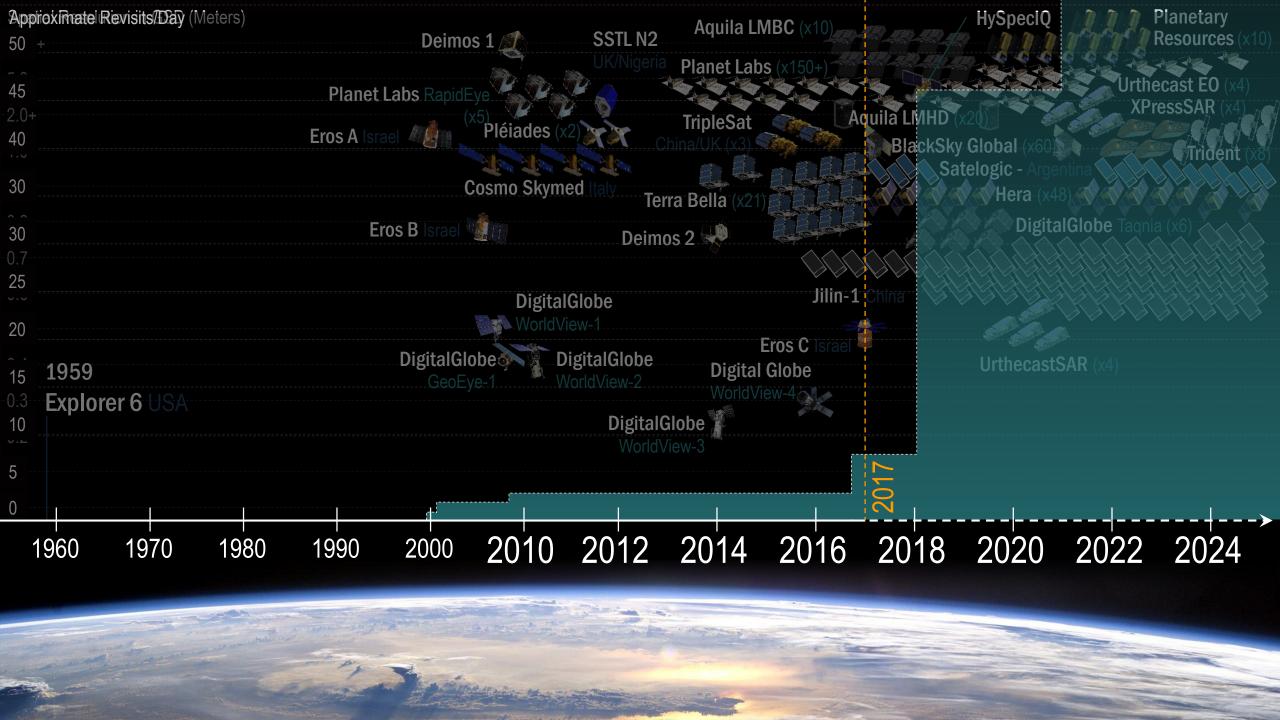


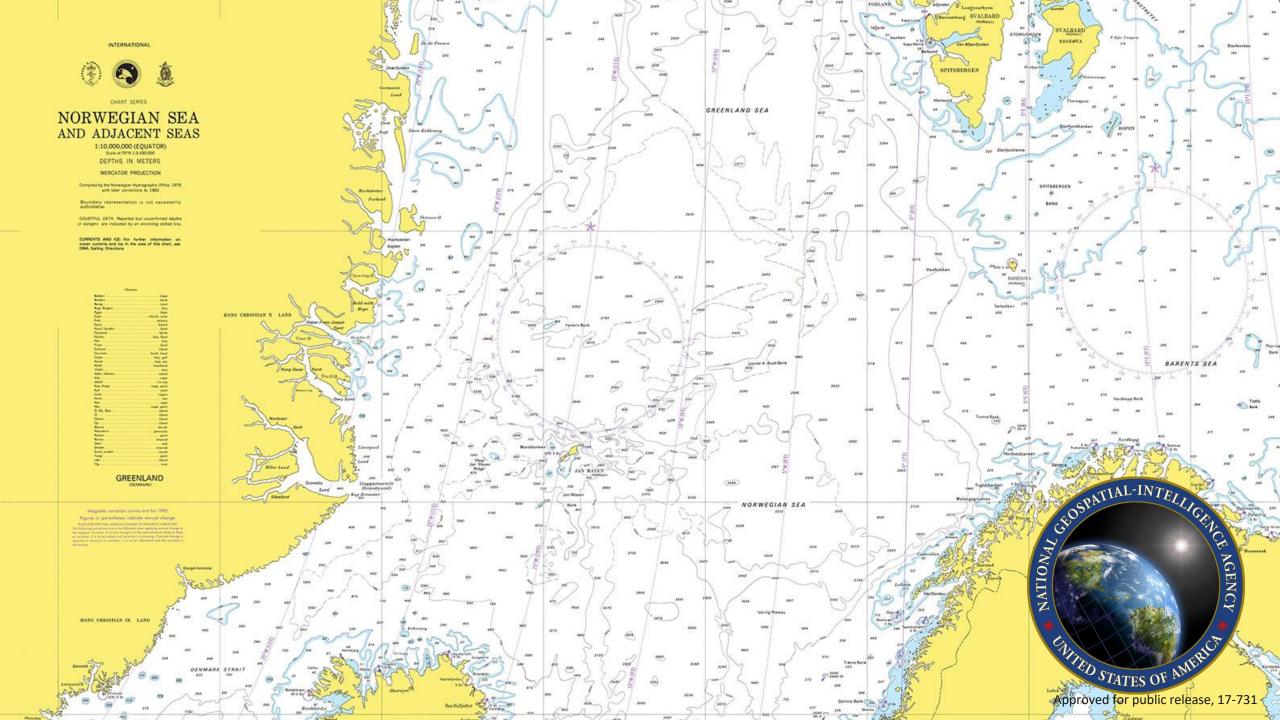
Geospatial Intelligence (GEOINT) - Automation, Artificial Intelligence and Augmentation (AAA)

William "Buzz" Roberts

27 November 2018









NGA By The Numbers



196 MILLION

SQUARE KILOMETERS OF PRECISE STEREO AND MONO-ORTHORECTIFIED IMAGERY

1.2 Billion Features

204,000 Standard Maps

70 MILLION HYDROGRAPHIC FEATURES

5,000 Nautical Charts

3,900 Digital Nautical Charts Libraries

24/7 Worldwide Navigation Warning Service

79 Nautical Publications

Notice to Mariners

4 BILLION AERONAUTICAL DATA ELEMENTS

48,000 Airfields in Automated Air Facilities Intelligence File

32 Million Vertical Obstructions

22,000 Instrument Flight Procedures in Digital Aeronautical Flight Information File

3,000 DOD Flights per Day

125 MILLION GRAVITY RECORDS

World Geodetic System 1984 Reference Frame

270 Million Square Kilometers of Elevation Data Coverage

Foundation for all DOD and Positioning, Navigation, and Timing

11 MILLION GEOGRAPHIC NAMES

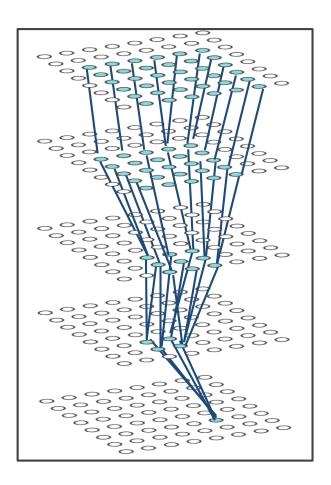
15,000 Human-Geography-Related Feature Classes

50,000 Maritime and Land Boundaries



Deep Learning – A Powerful New Hammer

Theory



Massive labeled data



Photos-iStock.com

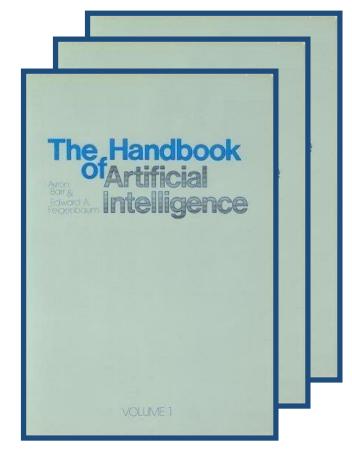
Cheap powerful computers





Artificial Intelligence / Machine Learning

- Long, mostly academic, history
- Limited, but profound, successes
- Narrow AI (i.e., ML) has shown value
- Much GEOINT well-suited for ML
- ML performance not well understood
- USG R&D continues to play key role



Three volumes, originally Published in 1985



GEOINT Application Examples

- Exploit scene knowledge
- Automate mundane enable analysis
- Support D&D defeat
- Handle massive, multimodal data

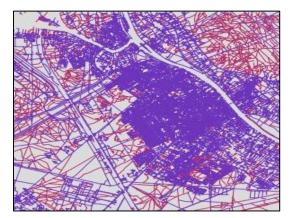




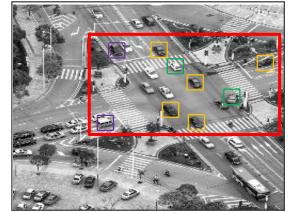
https://en.wikipedia.org/wiki/Military_dummy
This is a file from the Wikimedia Commons



https://en.wikipedia.org/wiki/Military_dummy
This is a file from the Wikimedia Commons



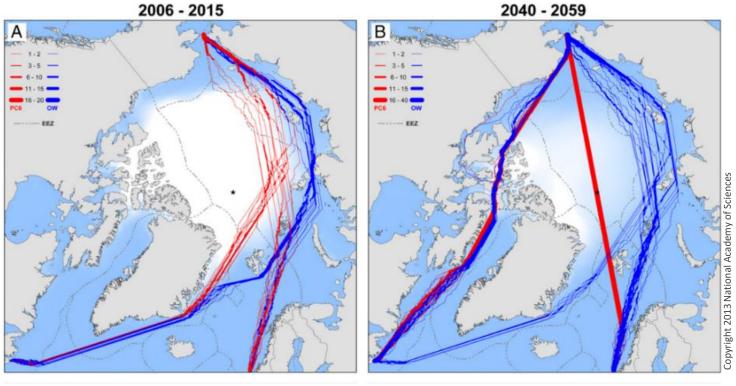
Source: Vector Data Sources: OpenStreetMap (OSM) public data; NGA Feature Foundation Data (FFD), Approved for Public Release, 15-373



Sydney, Australia- iStock.com



Arctic Travel Routes

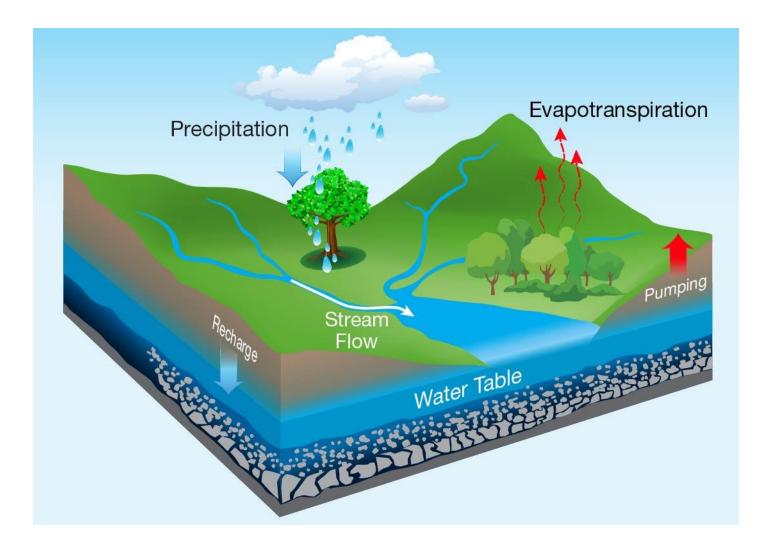


Red: transit routes for medium icebreaker **Blue**: transit routes for open water vessel

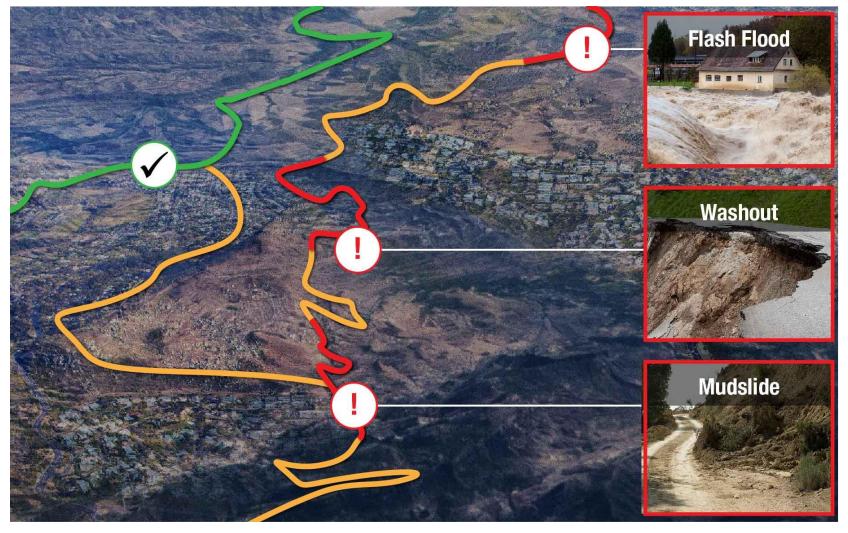
Develop a weather-related risk assessment analytic for arctic routes



Water Budget Prediction

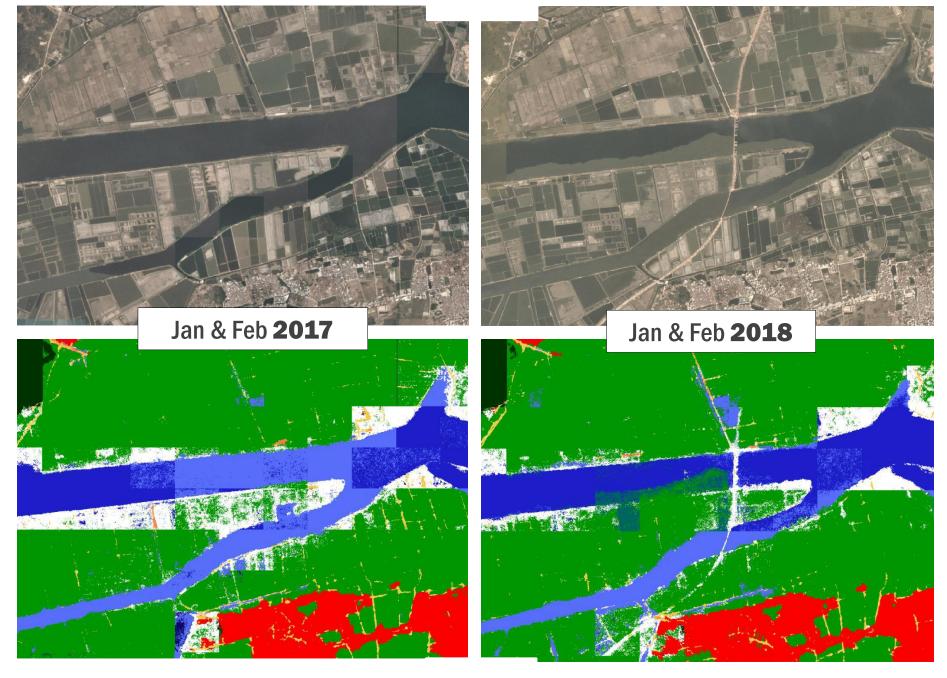


Mission Routes



Develop a weather-related risk assessment analytic for routes





Machine Learning: The High-Interest Credit Card of Technical Debt

D. Sculley, Gary Holt, Daniel Golovin, Eugene Davydov,
Todd Phillips, Dietmar Ebner, Vinay Chaudhary, Michael Young
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Google, Inc

Abstract

Machine learning offers a fantastically powerful toolkit for building complex systems quickly. This paper argues that it is dangerous to think of these quick wins as coming for free. Using the framework of *technical debt*, we note that it is remarkably easy to incur massive ongoing maintenance costs at the system level when applying machine learning. The goal of this paper is to highlight several machine learning specific risk factors and design patterns to be avoided or refactored where possible. These include boundary erosion, entanglement, hidden feedback loops, undeclared consumers, data dependencies, changes in the external world, and a variety of system-level anti-patterns.

Date of publication: 2014



Issues

- AI/ML technology & expertise available worldwide
 - Relentless focus on differentiation
- Novel software not robust
 - Security must be a priority
- Limited training data
 - Partnerships (e.g., SpaceNet, xView), transfer learning
- ML success & failure modes not well understood
 - Theory and experimentation essential



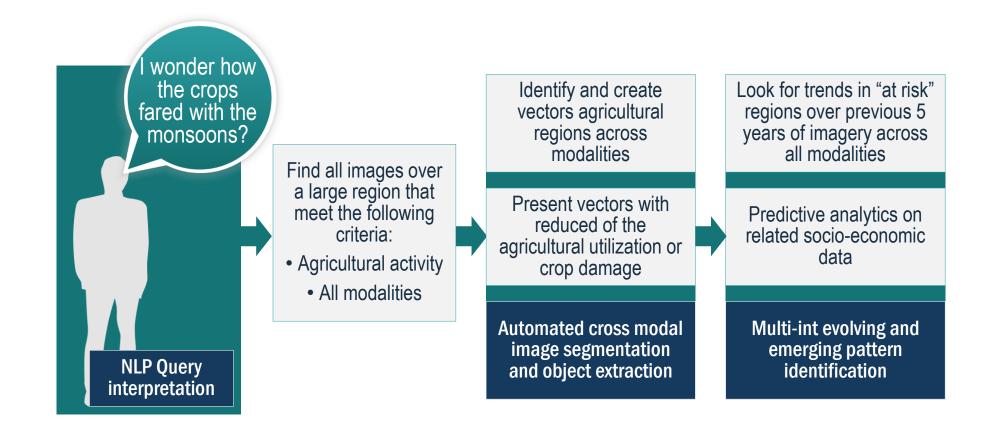
Opportunities



- GEOINT automation is required
 - ► ML good match for automating fundamental extraction
- Massive training data are required
 - ► NGA is uniquely situated to help provide
- Significant expertise and innovation required
 - Industry, academia and federal R&D aggressively investing



Challenge





Cross-modality target signature prediction



- Using target observations in one modality, predict material properties and response in other modalities
- Rapidly generated prediction is key to generating volumes of data needed for Machine Learning training and for predictions to serve as a manual analysis aid



Most Recent Examples of Adversarial Attacks on Deep Learning

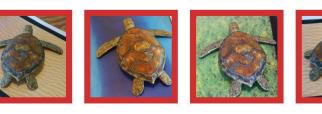
One-Pixel Attacks (24 October 2017, Kyushu University, Japan)

Automobile Cat(Dog) Airplane(Dog) Automobile(Dog) Dog(Ship) (Airplane) It's a Turtle Deer(Dog) Frog(Dog) Frog(Truck) Dog(Cat) Frog(Truck) Horse Dog(Horse) Ship(Truck) Ship(Truck) Horse(Cat)

74% of images misclassified with 98% confidence Black-box attack

(Automobile)

Real 3D Objects (30 October 2017, MIT)



It's a Rifle







Adversarial Patch

Brown, Mane, Roy, Abadi, Gilmer NIPS 2017





It's All About The Data





NGA Research

A trusted partner and source of powerful new capabilities

- ▶ Automate
- **▶** Enrich
- ▶ Assure
- ▶ Compute
- ▶ Transition



Ensuring The Unfair Fight





